Spatiotemporal Analysis of Brain Functional Connectivity

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Abstract— **Brain functions are based on interactions between neural assemblies distributed within and across distinct cerebral regions. During cognitive tasks, these interactions are dynamic and take place at the millisecond time scale. In this context, the excellent temporal resolution (<1 ms) of the Electroencephalographic –EEG- signals allows for detection of very short-duration events and therefore, offers the unique opportunity to follow, over time, the dynamic properties of cognitive processes.**

In this paper we propose a new algorithm to track the functional brain connectivity dynamics. During picture recognition and naming task, this algorithm aims at segmenting high resolution (hr) EEG functional connectivity microstates. The proposed algorithm is based on the *K-means* clustering of the connectivity graphs obtained from the Phase Locking Values (PLV). Results show that the algorithm is able to track the brain functional connectivity dynamics during picture naming task.

Keywords—**High resolution EEG, PLV, *K-means*, functional connectivity dynamics.**

I. Introduction

A key challenge in neuroscience is to identify distinctive networks underlying specific brain functions, from data provided by neuroimaging techniques, which can be either structural (diffusion imaging, DTI) or functional (electroencephalography, -EEG magnetoencephalography –MEG- or even functional magnetic resonance imaging fMRI-). These neuroimaging techniques can be used to identify brain networks involved in normal brain functions(behavioral response to stimulus, learning , memory) as well as in neurological disorders like epilepsy, Alzheimer, Schizophrenia[1].

In this context, fMRI has significantly evolved over the past two decades and is now commonly used to characterize brain connectivity. However, the short duration of cognitive processes (~500ms for the picture naming, for example) requires the use of techniques that have a very high time resolution (on the order of ms), which is not the case of fMRI (~1s), although it has the advantage of having excellent spatial resolution.

Several studies have indicated that the use of electroencephalography (EEG) –which provides scalp signals at excellent temporal resolution (sub-millisecond) - combined with appropriate signal processing techniques can bring relevant information about normal networks activated during cognitive activity[2] or about disturbed networks associated for instance with tumors[3].

This excellent temporal resolution allows us to analyze the dynamic properties of the cognitive process, a challenging issue so far addressed in a few studies only. In[4, 5], proposed algorithms were based on the Event Related Potentials (ERPs) amplitude. However, these algorithms do not take into account the connectivity between signals (electrode space) or brain regions (source space). Other methods rely on the decomposition of EEG measurements into topographic and time-frequency elements. These methods based on frequency analysis, show that a large set of data can be represented by a small number of topographic distributions [6].Again, these methods ignore the connectivity aspects.

Regarding the results based on the connectivity analysis, most of reported methods make use of a constant time window to track the EEG dynamic connectivity. This window is chosen empirically or based on a priori information about the analyzed task [2]. A few attempts have been recently reported to avoid this constraint [7, 8].However, most of the proposed algorithms are not adequate to track changes over very short durations (as in the case of responses evoked by visual stimuli).

In this paper, we propose a new algorithm to track the brain functional connectivity dynamics during picture naming task. The proposed algorithm is based on the K-means clustering of the connectivity graphs obtained by the trial by trial Phase Locking Values (**PLV**) method.

II. Materials and metthods

A. DATA

Six subjects were shown pictures on a screen using E-Prime 2.0 software (Psychology Software Tools, Pittsburgh, PA). They were asked to name the displayed objects. The

148 images were selected from a database of 400 pictures standardized for French[9] and were used during two sessions (about eight minutes each) of 74 stimuli. The brain activity was recorded using an hr-EEG system (256 electrodes, EGI, Electrical Geodesic Inc.). EEG signals were collected at a 1 kHz sampling frequency and were band-pass filtered between 3 and 45 Hz. Each trial was visually inspected, and epochs contaminated by eye blinking, movements or any other noise source were rejected and excluded from the analysis performed using the EEGLAB open source toolbox[10]. This study was approved by the National Ethics Committee for the Protection of Persons (CPP), (*conneXion* study, agreement number 2012-A01227-36, promoter: Rennes University Hospital). We excluded the electrodes located on the face as well as the few electrodes showing too high impedance. Overall, in our hr-EEG montage, 180 (over 256) electrodes were retained as providing excellent quality signals over all subjects.

B. Functional connectivity measure

Functional connectivity is defined as the temporal correlation (wide sense) among the activity of different neuronal assemblies. Several methods have been proposed to characterize the brain functional connectivity. In this paper we used the phase locking value (**PLV**) method proposed by Lachaux et al. [11]to measure synchronization on a trial by trial basis. For each channel pair, *x* and *y*, at time *t*, and for all the trials (n=1…N), **PLV** is defined as:

$$\mathrm{PLV}_{xy} = \frac{1}{N}\left|\sum_{n=1}^{N} \varphi_x - \varphi_y\right| \qquad (1)$$

Where φ_x and φ_y are the unwrapped phases of signals *x* and *y* respectively. We applied a normalization procedure so that the PLV_{xy} values were compared with the 200ms baseline preceding the presentation of the image. Let μ_{xy} and σ_{xy} be the mean and standard deviation computed from a 200ms pre-stimulus baseline. The normalized **PLV** is then computed as $\mathrm{PLV}_{xy} = (\mathrm{PLV}_{xy} - \mu_{xy})/\sigma_{xy}$. The connectivity matrices are computed in the low gamma frequency band (30 Hz - 45 Hz). A thresholding procedure is then applied on the functional connectivity values in order to retain a small fraction (10%) of the strongest functional connections, as discussed in [12].

C. Segmentation algorithm

The proposed algorithm can be summarized as follows:

1- Compute the adjacency matrices for each subject using **PLV** to obtain *T* connectivity graphs. The instantaneous averaged connectivity **PLV (t)** is computed over all the subjects.

2- Select randomly *K* graphs (*K* varies from 3 to-10) from the *T* graphs. To avoid the choice of very close graphs , an additional constraint has been added which consists in rejecting the *K* graphs if the time interval between two graphs in any pairs is less than 30 ms.

3- Calculate the spatial correlation **(sC)** between each of the *K* and *T* graphs. **sC** is computed based on **PLV(t)**. For two pairwise PLV P and Q, at instant *t*, **sC(t)** is defined as:

$$\mathrm{sC}_{P,Q}(t) = \frac{\sum_{i=1}^{M} P_i \cdot Q_i}{\sqrt{\sum_{i=1}^{M} P_i^2} \cdot \sqrt{\sum_{i=1}^{M} Q_i^2}} \qquad (2)$$

Where *M* is the number of combinations (180x(180-1)/2).

4- From these spatial correlation values, the Global Explained Variance **(GEV)** is calculated as defined in[5]. While **GEV** is unstable (i.e. doesn't reach its highest value over the iterations), the template maps are redefined averaging all the graphs yielding to the same cluster. When reaching the highest **GEV**, *K*+1 template maps are then selected and all the above procedure is repeated. To choose the optimal number of template graphs, we use a method based on the Cross Validation **(CV)** criterion as introduced in[5] which is the ratio between **GEV** and the degrees of freedom for a given set of graphs. Its minimum gives the optimal number of segments. Finally, an additional constraint is used to prevent the small clusters, a given connectivity graph must "survive" for at least 30ms.

5- The result obtained in the averaged data is then compared with the moment-by-moment connectivity graphs of individual subjects PLVs. Each time point is labelled according to the graph with which it best correlates, yielding a measure of graph presence. This procedure referred to as 'fitting' allows for establishing how well a cluster map explains individual activity and its duration.

III. RESULTS

To start with, after the random selection of the template graphs, we compute the spatial correlation between these

template maps and all the graphs. An example of the **sC** curves (at each instant) is shown in Fig. 1 for 3 random different instants. The figure shows how **sC** is able to detect the spatial correlation between graphs. We can notice also that around the highest correlation peak, the correlation values are higher than temporary distant graphs.

This step is followed by the computation of **GEV** for different template graphs. In our study the number of clusters varies from 3 to 10 clusters. The lowest **CV** value is obtained for a number of clusters equal to 6.

We then choose this number of clusters to identify the spatiotemporal behavior of the connectivity graphs obtained with the algorithm.

Results are exemplified in Fig. 2. The figure shows the segmentation of **ERP** signals (180 channels) into 6 clusters. The first cluster corresponds to the period from 0(onset) to 116 ms. In this cluster, we can observe a network located in the occipital lobe.

A shorter graph is then observed between117 and 153ms with also strong connections at the occipital and temporal lobe. The 3rd cluster is located at 154 -190 ms where strong connections appear in the temporal and parietal lobes. A network appears in the cluster 191-316ms with the presence of connectivity in frontal regions, followed by a cluster (317-480 ms) with dense connectivity in frontal and occipital regions.

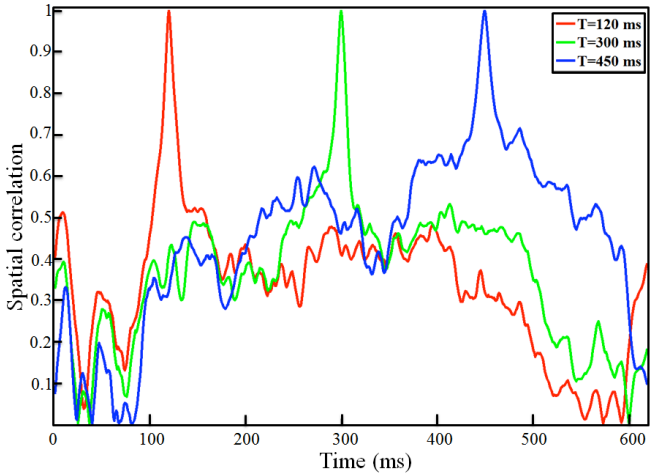

Fig1.Spatial correlation (**sC**) of 3 templates (t=120, t=300, t=450) with all the others graphs (*T*).

The networks (481-620 ms) then become denser in temporal left and frontal regions.

Table 1 shows the results obtained after the 'fitting' process which consists in testing the inter-subject variability. The map presence values are presented in column, the templates (T3, T6) have high values of maps presence between subjects (73%, 78%) and low values in the template (T1, T4).

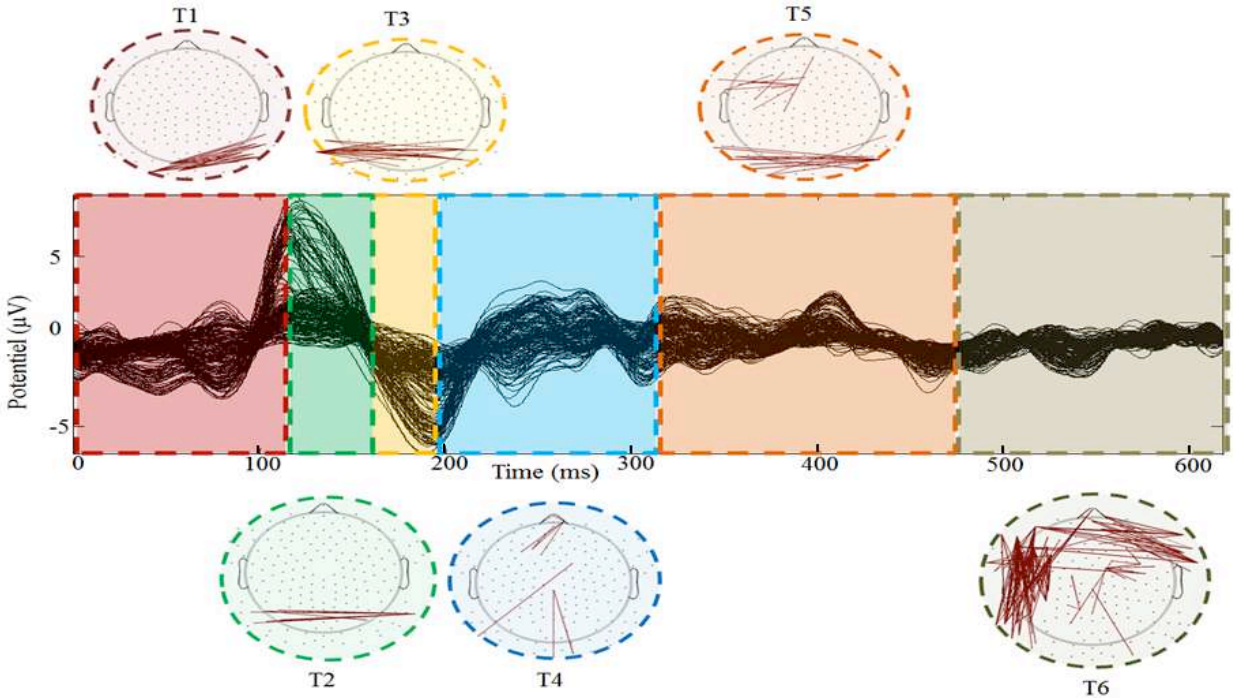

Fig 2.Event Related Potentials (180 electrodes) for the picture naming task and temporal distribution of the functional connectivity graphs revealed by spatio-temporal segmentation algorithm detailed in the paper. Connectivity graphs and their specific time windows are showed by each rectangle.

Table1

Mean and standard deviation of the map presence after the fitting step.

	T1	T2	T3	T4	T5	T6
Map presence	31%±16	41%±38	73%±30	23%±28	39%±22	78%±32

IV. Discussion

Preliminary results were presented to demonstrate that the proposed algorithm can be used to track the dynamics of the brain functional connectivity. Very interestingly, results are qualitatively consistent with the state of the art of the analyzed task regarding the activation starting in the occipital lobes during picture recognition followed by activation in the temporo-frontal regions[13].One of the challenge faced by our study is to specify the maximal number of clusters. The increase of the maximal number of clusters increases the computation cost. In our study we used 10 clusters. A classical and still unsolved difficult question relates to the setting of threshold values applied on the connectivity matrices. In our study, the chosen threshold value was 10%, [12]. Other approaches can be explored like those based on surrogate data[2], although requiring an even higher computation time. Finally, this algorithm is a good start to then compare the dynamics of the brain connectivity for two different cognitive tasks such as the difference between spelling[14] and naming task which is our ongoing work. Also the algorithm will be applied on EEG source connectivity graphs to track brain functional connectivity dynamics at cortical source level.

V. Conclusion

In this paper we proposed a new algorithm to track the functional brain connectivity dynamics and segment hr-EEG signals recorded during picture recognition and naming task using *K-means* clustering of the connectivity graphs. This algorithm shows good performance to demonstrate the stability of the functional brain connectivity overs some short periods of time and to segment the cognitive process into functional connectivity microstates.

Acknowledgements

This work has received support from European Research Council (ERC) and from French government granted to the CominLabs excellence laboratory and managed by the National Research Agency in the “Investing for the Future" program under reference Nb. ANR-10-LABX-07-01.

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